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## Impacts of COVID-19 on public transit ridership

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### ABSTRACT

In this paper, a national-wide study is conducted to investigate the impacts of COVID-19 on the public transit ridership in the top twenty metropolitan areas in the U.S. At first, COVID-19 composite index was developed to qualitatively measure the level of public fear toward COVID-19 in different metropolitan areas. After that, to analyze the impact of COVID-19 and some socioeconomic factors on transit ridership reduction during the COVID-19 pandemic, a random-effects panel data model was developed and the traditional correlation analysis was also conducted. According to the results of both analyses, it was found that the areas with higher median household income, a higher percentage of the population with a Bachelor's degree or higher, higher employment rate, and a higher percentage of the Asian population are more likely to have more reductions in public transit ridership during the COVID-19 pandemic. On the other side, the areas with a higher percentage of the population in poverty, and a higher percentage of the Hispanic population are more likely to experience smaller reductions in public transit ridership.

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### Introduction

The widespread COVID-19 has led to profound impacts on our society, economy, and transportation systems. It has the-  
atrically altered public travel behavior worldwide and posed a great challenge for public transportation operations worldwide.

According to Transit Data collected from public transit agencies in April 2020, the ridership levels across all public transit modes have been decreased by 73% in the United States, especially the light rail mode has been reduced by nearly 90% (Transitapp, 2020; EBP, 2021). The sharp decline in the number of passengers will affect the operation of public transit and tighten the funding sources. Meanwhile, public transit is critical for citizens to access essential services such as food or medical services and it will remain at the core of transport systems that keep people moving and keep our cities running. Therefore, understanding the impacts of COVID-19 on public transit ridership will be critical for transportation planning to make the right decisions for maintaining safe and effective public transit services under such special circumstances. Some previous studies have conducted regional-specific analyses of the impacts of COVID-19 on the ridership of a particular transit system (Hu and Chen, 2021; Wilbur et al., 2021; and Brough et al., 2020). A national-wide study is needed to investigate the impacts of COVID-19 in different metropolitan areas across the U.S. In addition, most existing studies simply used COVID-19 confirmed cases and(or) confirmed deaths as indexes in their analysis. A composite index that can better measure the level of

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public fear toward COVID-19 of an area or the level of public fear toward COVID-19 needs to be used for the model development. Furthermore, previous studies have found that the magnitude of impacts of COVID-19 varied across different socioeconomic groups (Hu and Chen, 2021; Wilbur et al., 2021; and Brough et al., 2020). Thus, the equity problem caused by COVID-19 needs to be further investigated based on nationwide data. To fill these gaps, this research is to investigate the impacts of COVID-19 on the public transit ridership in the top twenty metropolitan areas in the U.S. To this end, the following specific research objectives have been set up:

- (1) Develop a COVID-19 composite index that can quantitatively measure the level of public fear toward COVID-19 in an area.
- (2) Develop an advanced mathematical model to analyze the impacts of COVID-19 and some socioeconomic factors on transit ridership reduction during the COVID-19 pandemic.

This study is among the first research to use a COVID-19 composite index in modeling the impacts of COVID-19 on public transit ridership change. In this study, we collected and analyzed the public transit (bus and light rail) ridership data for the top twenty metropolitan areas in the United States. Through a comprehensive literature review, the reasons for transit ridership decline and the impacts of COVID-19 on different sociodemographic groups are discussed. After that, an panel data model was developed to identify the factors that affect the public transit ridership reduction during the COVID-19 pandemic. Finally, conclusions are provided.

## Background and literature review

It is been over one year since the outbreak of COVID-19, a number of studies have been conducted on the impact of COVID-19 on public transit ridership in different aspects. Based on the review of these existing studies, the following three topics are discussed: (1) transit ridership decline and reasons, (2) impacts of COVID-19 on different sociodemographic groups, and (3) methodology for analyzing the impact of COVID-19 on public transit ridership.

### *Transit ridership decline and reasons*

Declines in transit ridership during the COVID-19 pandemic have been observed across the world (Transitapp, 2020; EBP, 2021; WMATA, 2020). For example, in Washington DC, Metrorail ridership was declined at a maximum of 90%, and bus ridership was declined at a maximum of 75%, subway ridership decreased by 77%, compared with the transit ridership in 2019 (WMATA, 2020). In Britain, the COVID-19 outbreak has led to a 90% drop in rail travel and 94% and 83% reductions in tube and bus journeys in London respectively (Carrington, 2020). Averagely, the COVID-19 pandemic has caused a 72.4% reduction in ridership for 95% of stations in Chicago Hu and Chen (2021). Various factors on both the demand side and supply side cause the sharp drop in transit ridership during the COVID-19 pandemic.

### *Demand-side reasons*

On the demand side, first, the lockdown and stay-at-home orders abruptly cut the trips in many cities (Wibur et al., 2020). Second, during the pandemic, many businesses allow their employees to work at home and many schools provide virtual learning options to their students, which further reduced the demand for work-related trips. Third, since public transit involves collectively moving a group of passengers in an enclosed space, it may increase the risk of COVID-19 transmission (Zheng et al., 2020). To minimize exposure to risky environments, travelers intensively avoid riding public transit. They shifted from public transit to passenger cars and other modes. For example, in the early days of the pandemic, the fears of infection may have spurred car purchases in New York City and the car travel was quicker to recover than any form of public transit during the pandemic (Penney, 2021). Also, Capgemini Research Institute has conducted a survey of 11,000 consumers from 11 countries and found that 46% of respondents plan to use their car more frequently and make less use of public transport (Winkler et al., 2020). Furthermore, Teixeira and Lopes (2020) found that “there is some evidence of transit users shifting to the shared bike programs” in New York City.

### *Supply-side reasons*

On the supply side, due to the social distancing directives and other safety protocols to prevent the spread of coronavirus, and public transit agencies have to reduce their service capacity. For example, to keep social distance, all public transit agencies reduced vehicle capacity from 25% to 75% to keep passengers at least 6 feet distance from each other. For example, Houston reduced 50% by tagging the other seats as unavailable (see Fig. 1). New York, Washington DC, Phoenix, Minneapolis and Baltimore reduced 75% capacity; St. Louis reduced 25% capacity (MTA, 2020; WMATA, 2020; VMTS, 2020; Minneapolis Metro Transit, 2020; Maryland Transit Administration, 2020). In addition, during the pandemic, due to the insufficient transit workforce, the sharp drop in fare revenue, and the strengthening of cleaning procedures, many transit agencies reduced their service hours and routes, and keep essential functions only (DeWeese et al., 2020). For example, Los Angeles trimmed service by



Fig. 1. Placards on Bus for Keeping Social Distancing (Source: METRO, 2020).

about 10% (Los Angeles County MTA, 2020). By mid-April 2020, King County Metro had made three rounds of service adjustments and was operating 27% fewer service trips than its typical weekday service (Switzer, 2020). The reduced service caused longer waiting times at transit stations and more crowded buses/trains for some transit lines, which will cause further ridership reduction and more trip shifts from public transit to other modes.

#### Other factors

Some other unobserved factors like government policies and vaccination rates may also contribute to the change of the public transit ridership. For example, as COVID vaccination becomes widespread, there is a recovering trend in public transit ridership (George et al., 2021). In addition, mandatory mask order and mask compliance rates may also affect the public transit ridership. These factors need to be investigated when more data become available.

#### Impacts of COVID-19 on different sociodemographic groups

Research has shown that the impacts of COVID-19 on public transit are different among different sociodemographic groups due to the different abilities of different groups of individuals to adjust their travel behavior in the face of the challenges of pandemic and various changing policies (Brough et al., 2020). For example, the people who work in information, management, and technology-related positions are more likely to be able to work from home while the people who need to be present to work in person still need to travel to work (Tan et al., 2020). Survey results indicate that ridership of public transportation in Santiago reduced by about 30% to 40% for low-income households, while for high-income households, the reduction of ridership was more than 70% (Tirachini and Cats, 2020). Several studies have found that areas with more lower-income, lower-educated, and people of color households had fewer declines in the ridership of public transit during the COVID-19 pandemic. Brough et al. (2020) found that at the initial stage of the pandemic in King County, Washington State, high-income residents are disproportionately switching from public transportation to cars. However, over time, the differences in the travel behavior of different socio-economic groups have reduced. It was also found that the travel reduction is less among less-educated and lower-income individuals even taking into account the model substitution and the reduction of differentiated public transportation services. Wilbur et al. (2021) found that the high-income areas of Nashville City showed a reduced transit ridership of more than 19% compared to the low-income areas in that city. Hu and Chen (2021) found that the ridership of the “L” train system in Chicago has reduced more in regions with more commercial lands and a higher proportion of white people, educated, and high-income people, while regions with more employments in trade, transportation, and utility sectors or with more COVID-19 cases/deaths show smaller reductions in ridership.

These previous studies have discussed the underlying causes of the socio-economic gap in the changes in public transit ridership. First, low-income and historically marginalized groups tend to be more reliant on public transportation. Pucher and Renne (2003) found that minorities and low-income households account for 63% of transit riders in the United States. Second, during the pandemic, the essential workers must go to the workplace irrespective of the stay-at-home order. A recent analysis found that essential workers account for about 36% of total transit passengers in the United States (TransitCenter, 2021). Most of the essential workers are non-white and have low incomes Hu and Chen (2021). In addition, the less-educated and lower-income people are relatively incapable of working remotely. The home conditions of the less-educated and lower-income groups are generally less hospitable for work or study at home due to “lack of adequate internet access, space constraints, and limited access to outdoor areas” (Brough et al., 2020).

### Methodologies for analyzing the impact of COVID-19 on public transit ridership

Different types of statistical methods have been used to analyze the impact of COVID-19 on public transit ridership. First, the traditional correlation analysis method has been used for identifying the factors that are strongly correlated with the ridership decline of public transit during the pandemic (Wilbur et al., 2021). Correlation analysis is a good method for quantifying the strength of the linear relationship between a pair of variables. However, it cannot account for the collective effects of multiple variables. To address this problem, many studies have used the multivariable linear regression in transit ridership analysis. Ahangari et al. (2020), Brough et al. (2020), and Liu et al. (2020) used the ordinary least squares (OLS) regression method to analyze the factors that are affecting transit ridership changes during the pandemic. The limitation of the traditional regression model is that it assumes that all observations are independently and normally distributed, which may not always be true. Therefore, advanced methods have been used. For example, Hu and Chen (2021) used the partial least squares regression to model the impacts of various factors such as land use, COVID-19 virus-related, socioeconomic, and transit service on the ridership reduction. The partial least squares regression is good for addressing the multicollinearity problem in the regression model. However, there are some gaps in the existing studies.

- First, in order to assess the impact of COVID-19, a quantitative indicator for measuring the level of public fear toward COVID-19 in an area needs to be developed first. In general, two COVID-19 indexes have been commonly used: confirmed cases and confirmed deaths. Some studies simply use one of these indexes or use both indexes in their models. Since the number of confirmed cases or deaths is highly related to the type and population size of an area (a big city tends to have more cases than a small town), use the absolute number of cases or deaths will affect the model transferability. In addition, since these two indexes are highly correlated, simply include both two indexes in the model would undermine the modeling results. Liu et al. (2020) has used the Google search trend index for the keyword “Coronavirus” to measure public awareness and concern about the COVID-19. This measure may be able to reflect the level of public awareness at the beginning of the pandemic. However, as time goes by, people become more familiar with COVID-19 and its information resources, the number of searches will decrease. Therefore, a composite index that can better measure the level of public fear toward COVID-19 of an area needs to be developed.
- Second, in most of the public transit studies, the transit ridership data were collected from different metropolitan areas during different periods. For example, in Liu et al. (2020), daily transit ridership data were collected from 113 county-level transit systems in 63 metro areas from February 15th to May 17th, 2020. The observations from the same area are very likely to be correlated. Therefore, the assumption of the traditional regression model that all observations are independently distributed may not be held. To address this problem, the panel data modeling approach can be used to model the cross-sectional observations in different periods.

To fill these two identified gaps, in this study, a composite index was developed to measure the level of public fear toward COVID-19 in an area and a random-effects panel data model was developed to analyze the impacts of COVID-19 and some socioeconomic factors on the ridership reduction during the pandemic.

### Data description

In this study, we investigated the change of public transit ridership for 1 year from February 1st 2020 to January 31st, 2021 since the World Health Organization (WHO) issued a global health emergency on January 30th, 2020. Three different types of data were collected: (1) COVID-19 cases and deaths data during the study time period, (2) public transit ridership data from February 2019 to January 2021, and (3) sociodemographic data of the selected metropolitan areas during the study time period. The COVID-19 case and deaths data were collected from USA FACTS official website (USAFacts, 2020). The ridership data are the monthly public transit ridership data collected by the National Transit Database (NTD) from the Federal Transit Administration (FTA) (NTD, 2020). The sociodemographic data of the studied metropolitan areas was retrieved from the American Community Survey (ACS) 1-year estimates data profile (United States Census Bureau, 2019).

The COVID-19 case and deaths data included all COVID-19 the daily confirmed cases by counties and by states. Note that, since the COVID-19 data is county-based instead of metropolitan-based, in this study, county-based cases and deaths within each metropolitan area were aggregated to derive the metropolitan-based cases and deaths. For the public transit ridership data, we focus on the impacts of COVID-19 on the bus and light rail transit modes in the study areas. Different types of buses were considered, including motorbus (MB), Commuter Bus (CB), and Bus Rapid Transit (RB). The ridership is reported as the number of unlinked passenger trips, which are defined as the number of passengers who board public transit vehicles. As we mentioned before, the data was collected for the major transit agencies in the top twenty metropolitan areas based on their population. These top twenty metropolitan areas along with the major public transit agencies in these areas are presented in Table 1.

The dependent and independent variables used in this study were presented in Table 2, and the detailed explanations of these variables are provided in the following sections.



**Table 1**  
Summary of Studied Metropolitan Areas.

	Metropolitan Area	Population	Major Public Transit Agencies
1	New York-Newark, NY-NJ-CT	19,216,182	Metropolitan Transportation Authority
2	Los Angeles-Long Beach-Anaheim, CA	13,214,799	Los Angeles County Metropolitan Transportation Authority
3	Chicago, IL-IN Chicago	9,457,867	Chicago Transit Authority
4	Miami, FL	6,166,488	Miami-Dade Transit
5	Philadelphia, PA-NJ-DE-MD	6,102,434	Southeastern Pennsylvania Transportation Authority
6	Dallas-Fort Worth-Arlington, TX	7,573,136	Dallas Area Rapid Transit; Trinity Metro
7	Houston, TX	7,066,140	Metropolitan Transit Authority of Harris County
8	Washington, DC-VA-MD	6,280,697	Washington Metropolitan Area Transit Authority
9	Atlanta, GA	6,018,744	Metropolitan Atlanta Rapid Transit Authority
10	Boston, MA-NH-RI	4,873,019	Massachusetts Bay Transportation Authority
11	Detroit, MI	4,319,629	The Detroit Department of Transportation
12	Phoenix-Mesa, AZ	4,948,203	Valley Metro Transit System
13	San Francisco-Oakland, CA	4,731,803	San Francisco Municipal Transportation Agency
14	Seattle, WA	3,979,845	King County Metro; Sound Transit
15	San Diego, CA	3,338,330	San Diego Metropolitan Transit System
16	Minneapolis-St. Paul, MN-WI	3,640,043	Metro Transit
17	Tampa-St. Petersburg, FL	3,194,831	Pinellas Suncoast Transit Authority
18	Denver-Aurora, CO	2,967,239	Regional Transportation District
19	Baltimore, MD	2,800,053	Maryland Transit Administration
20	St. Louis, MO-IL	2,801,423	Metropolitan Saint Louis Transit Agency

**Table 2**  
Dependent and Independent Variables.

Variables	Description
<b>Dependent Variable</b>	
YoYMRRR	Year-on-Year (YoY) monthly ridership reduction rate
<b>Independent Variables</b>	
CI	COVID-19 Composite Index
Percentage of Poverty	Percentage of population under poverty thresholds
MHI	Median Household Income
Percentage of H.S. degree or higher	Percentage of population with High School degree or higher
Percentage of Bachelor's degree or higher	Percentage of population with Bachelor's degree or higher
Percentage of Non-English Speaking	Percentage of population who are Non-English Speaking
Percentage of Foreign-Born	Percentage of the population born in a foreign country
Percentage of Households No Vehicle	Percentage of households without a vehicle
Percentage of Taking Public Transit to Work	Percentage of the population takes public transit to work
Employment Rate	Percentage of the population employed
Percentage of Hispanic	Percentage of the Hispanic population
Percentage of White	Percentage of the White population
Percentage of Black	Percentage of the Black population
Percentage of Asian	Percentage of the Asian population

### Dependent variables

In this study, the dependent variable is Year-on-Year (YoY) monthly ridership reduction rate, which compares the ridership for a given month during the study period with the ridership in the same month of previous years. Take the first month, February 2020, as an example, the YoY ridership reduction rate of February 2020 can be expressed mathematically as follows:

$$\text{YOY Reduction Rate of Feb.2020} = \frac{\text{Monthly ridership of Feb.2019} - \text{Monthly ridership of Feb.2020}}{\text{Monthly ridership of Feb.2019}}$$

The derived YoY reduction rates of transit ridership of different metropolitan areas are presented in Fig. 2. As shown in this figure, all twenty public transit agencies have experienced a sudden ridership drop since March 2020 and then reached a stable level. It can be seen that all these areas suffered a 40–85% ridership reduction from March 2020 to April 2020. Among them, San Francisco-Oakland and Washington are the top two metropolitan areas with the highest ridership reduction rates. The ridership of New York has the sharpest decline at the beginning of the pandemic and it recovered a little bit and remain at around 60% YoY reduction rate during the rest of the time. Tampa-St. Petersburg has the relatively lowest ridership reduction rate at the beginning of the pandemic, but its reduction rate jumped to 70% in January 2021. From Fig. 2, it can be seen that overall the transit ridership for all areas has been reduced significantly. However, the reduction rate varies by time and area. In this study, we will use mathematical methods to investigate the impacts of COVID-19 on the ridership changes and other contributing factors to the ridership reduction in different metropolitan areas.

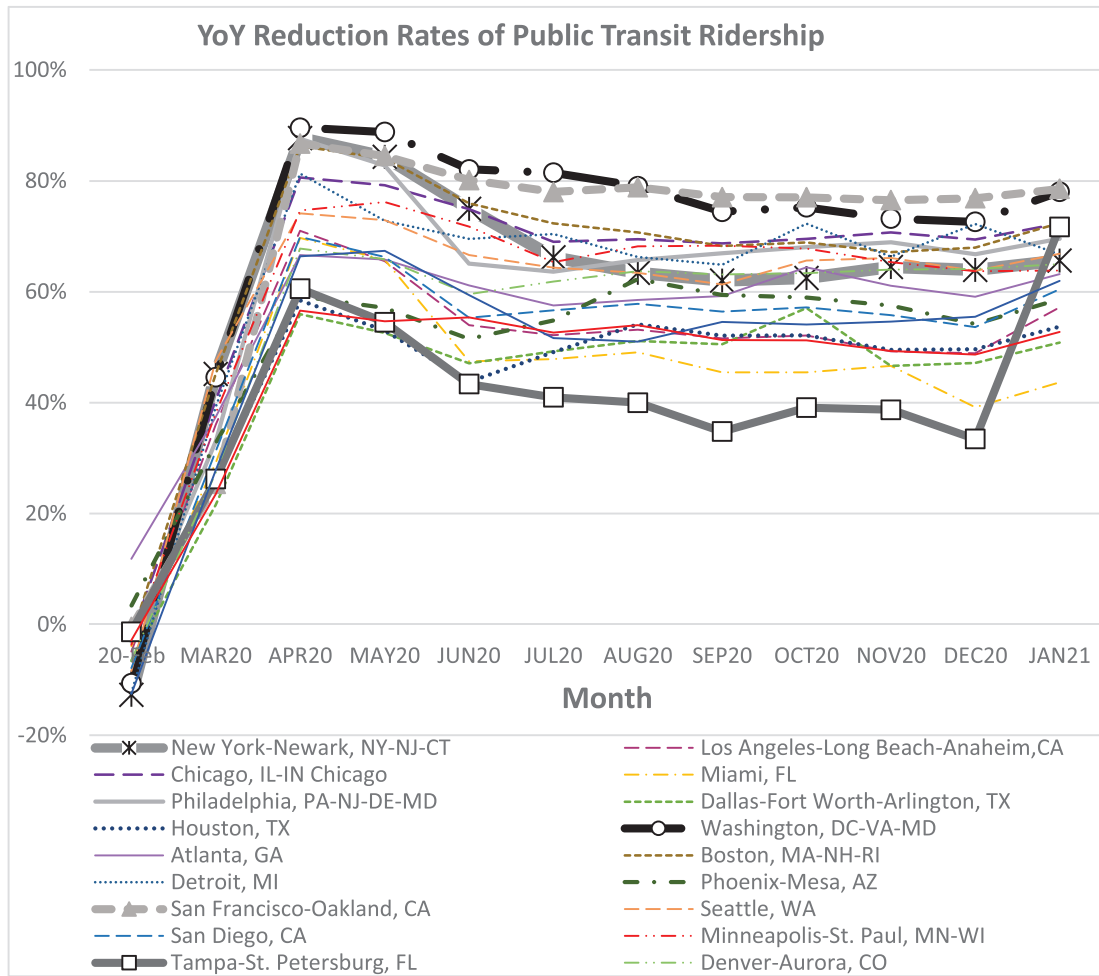


Fig. 2. YoY reduction rates of transit ridership of the selected metropolitan areas.

### Independent variables

Two types of independent variables are considered in this study: COVID-19 related factors and sociodemographic factors. The definitions of all the independent variables considered by this study are present in Table 2.

### COVID-19 composite index

To analyze the impacts of COVID-19, the level of public fear toward COVID-19 in a particular area need to be quantitatively measured at first. In the field of stock market prediction, a CI, also known as the global fear index, has been used in analyzing how many distortions in the market can be attributed to the pandemic (Khan et al., 2020). Salisu and Akanni (2020) also constructed a global fear index (GFI) for the COVID-19 pandemic to predict stock returns. Since the CI could provide a measure of public perceptions toward the pandemic, the COVID-19 CI proposed by Salisu and Akanni (2020) is used as an independent variable for measuring the level of public fear toward COVID-19 of the selected metropolitan areas in this study. Specifically, the CI for a metropolitan area  $i$  for a given day  $t$  can be developed by following three steps:

(i) Reported Cases Index (RCI):

$$RCI_t = \left( \frac{c_{i,t}}{c_{i,t} + c_{i,t-14}} \right) \times 100 \quad (1)$$

where  $c_{i,t}$  is the new confirmed cases at the current day  $t$  for the metropolitan area  $i$ ;  $c_{i,t-14}$  is the new confirmed cases at 14 days ago for the metropolitan area  $i$ . Because COVID-19 symptoms may appear 2–14 days after exposure to the virus (Centers for Disease Control and Prevention, 2021), this index measures the degree of deviation between the expected cases of reported cases in the next 14 days and the current reported cases. According to Equation (1), this index is in the range of 0

to 100, with the highest value representing the highest level of fear toward the pandemic, and the level of fear decreases as the index approaches 0 (Salisu and Akanni, 2020). Note that, if there are no changes during the past 14 days, this index will be 50. Similarly, the index for the reported death can also be derived as follows.

(ii) Reported Death Index (RDI):

$$RDI_t = \left( \frac{d_{i,t}}{d_{i,t} + d_{i,t-14}} \right) \times 100 \quad (2)$$

where  $d_{i,t}$  is the newly reported deaths at day  $t$  for the metropolitan area  $i$ ;  $d_{i,t-14}$  is the reported deaths at 14 days ago for the metropolitan area  $i$ . After that, by combining the calculated RCI and RDI, the COVID-19 Composite Index (CI) can be derived as follows

(iii) Composite Index (CI)

$$CI_t = [0.5(RCI_t + RDI_t)] \quad (3)$$

For each metropolitan area, the daily CI is calculated. Since the ridership data is monthly based, the daily CI was aggregated to derive the monthly average CI for each metropolitan area. The final CI results for each metropolitan area were presented in Table 3.

### Sociodemographic factors

The sociodemographic factors are area-based, that is to say, these factors vary with different metropolitan areas and remain the same within different periods. To find the factors affecting transit ridership, sociodemographic data related to the income, poverty, and education levels, and the racial/ethnic composition of each metropolitan area was obtained from the American Community Survey (ACS) 1-year estimates data profile (United States Census Bureau, 2019). These data were presented in Table 4.

## Methodology and results

### Random effects panel data model

As we mentioned in the literature review part, in this study, the panel data modeling method is used for analyzing the impacts of COVID-19 on the transit ridership reduction rate and the impacts of other socioeconomic factors.

Panel data refers to observations of the same cross-sectional units observed at multiple time points. A panel-data observation  $X_{it}$  has two dimensions:  $i = 1 \dots N$  denotes the cross-sectional unit and  $t = 1 \dots T$  denotes the time period of the observation. In this study, the data consist of information collected from 20 big metropolitan areas during 12 months. Thus, it is the panel data with 20 cross-sectional units observed during 12 time periods ( $N = 20$  and  $T = 12$ ). In general, the panel data model can be expressed mathematically as follows (Greene, 2000):

$$y_{it} = \alpha_i + \beta' X_{it} + \varepsilon_{it} \quad (4)$$

**Table 3**  
Average Monthly CI of the Studied Metropolitan Areas.

Metropolitan Areas	20-Feb	MAR20	APR20	MAY20	JUN20	JUL20	AUG20	SEP20	OCT20	NOV20	DEC20	JAN21
Atlanta, GA	0.00	36.21	60.95	49.57	48.61	58.76	48.44	43.72	49.92	50.18	56.81	53.76
Baltimore, MD	0.00	15.96	69.64	50.64	43.44	50.54	48.99	47.29	53.18	61.34	53.46	49.04
Boston, MA-NH-RI	0.00	34.55	75.46	38.32	38.36	49.70	46.76	54.08	57.98	55.66	48.49	56.43
Chicago, IL-IN	0.00	44.65	69.97	49.33	39.23	48.38	50.98	49.16	57.95	61.78	47.60	45.49
Dallas-Fort Worth-Arlington, TX	0.00	35.13	59.74	52.58	55.67	59.17	46.65	45.75	53.86	57.11	49.20	57.92
Denver-Aurora, CO	0.00	18.79	66.53	46.24	35.77	44.17	37.30	51.20	56.06	62.49	44.72	43.77
Detroit, MI	0.00	41.83	59.41	36.57	43.60	52.71	48.52	45.83	49.23	50.02	38.75	40.35
Houston, TX	0.00	19.18	62.90	47.57	64.22	59.47	48.03	41.64	45.92	54.04	50.15	60.45
Los Angeles-Long Beach-Anaheim,	0.00	40.61	69.96	51.28	52.59	52.35	45.89	44.70	49.87	58.81	61.03	52.76
Miami, FL	0.00	25.22	63.08	45.12	60.05	60.27	43.83	40.70	50.18	56.46	52.22	52.27
Minneapolis-St. Paul, MN-WI	0.00	12.37	65.91	59.85	41.35	45.64	51.85	48.23	52.67	56.65	46.97	43.95
New York-Newark, NY-NJ-CT	0.00	60.84	60.82	33.93	39.62	43.97	42.00	51.73	57.26	62.06	56.81	54.65
Philadelphia, PA-NJ-DE-MD	0.00	28.63	71.10	46.14	40.91	46.90	44.65	52.67	54.59	60.94	55.72	47.50
Phoenix-Mesa, AZ	0.00	19.14	61.61	52.17	61.53	56.23	35.28	42.89	49.97	56.41	44.20	58.83
San Diego, CA	0.00	15.97	56.72	43.35	44.84	42.47	34.82	41.85	43.47	40.19	52.58	46.45
San Francisco-Oakland, CA	0.00	32.75	56.74	45.65	49.96	52.74	49.68	46.04	47.95	53.66	57.55	52.83
Seattle, WA	3.45	84.06	49.95	39.88	51.84	48.39	48.01	31.72	44.29	40.79	22.49	36.50
St. Louis, MO-IL	0.00	19.30	62.03	48.15	41.61	53.52	49.33	49.54	50.47	58.85	45.35	48.95
Tampa-St. Petersburg, FL	0.00	22.40	43.51	52.17	63.76	54.81	44.53	43.29	48.77	55.34	53.49	52.06
Washington, DC-VA-MD	0.00	28.40	75.97	50.70	39.77	43.61	51.80	49.16	48.83	60.07	55.17	52.74



**Table 4**  
Sociodemographic Data for the Study Metropolitan Areas.

	Percentage of Poverty	Median Household Income	Percentage of Bachelor's degree or higher	Percentage of Non-English Speaking	Percentage of Foreign Born	Employment Rate	Percentage of Hispanic	Percentage of white	Percentage of Black	Percentage of Asian
New York-Newark, NY-NJ-CT	11.6%	83,160	41.8%	40.0%	29.7%	65.2%	24.6%	46.2%	15.6%	11.3%
Los Angeles-Long Beach-Anaheim, CA	12.4%	77,774	35.5%	54.4%	32.9%	65.5%	45.2%	29.8%	6.3%	16.0%
Chicago, IL-IN Chicago	10.6%	75,379	39.2%	29.4%	17.6%	66.8%	22.3%	52.9%	16.3%	6.5%
Miami, FL	13.5%	60,141	33.1%	55.1%	41.6%	63.6%	45.3%	30.4%	20.2%	2.4%
Philadelphia, PA-NJ-DE-MD	11.8%	74,533	39.0%	16.3%	10.9%	65.6%	9.5%	61.8%	20.4%	6.0%
Dallas-Fort Worth-Arlington, TX	10.5%	72,265	36.3%	32.2%	19.2%	68.8%	28.9%	46.7%	15.4%	6.7%
Houston, TX	12.9%	69,193	33.3%	40.1%	23.4%	66.5%	37.3%	36.3%	16.9%	7.8%
Washington, DC-VA-MD	7.5%	105,659	51.4%	29.6%	22.9%	71.5%	15.8%	45.4%	24.8%	10.2%
Atlanta, GA	10.5%	71,742	39.9%	18.6%	14.2%	67.0%	10.8%	47.2%	33.4%	5.8%
Boston, MA-NH-RI	8.6%	94,430	49.3%	25.2%	19.2%	69.5%	11.2%	70.4%	7.6%	7.9%
Detroit, MI	12.6%	63,474	32.4%	14.2%	10.3%	63.1%	4.4%	66.7%	22.2%	4.3%
Phoenix-Mesa, AZ	12.1%	67,896	32.2%	26.5%	14.3%	63.4%	31.0%	57.3%	5.1%	3.8%
San Francisco-Oakland, CA	8.2%	114,696	51.4%	41.3%	30.9%	67.8%	21.9%	40.3%	6.9%	26.0%
Seattle, WA	7.8%	94,027	44.1%	24.8%	19.7%	69.3%	10.1%	64.8%	5.6%	13.4%
San Diego, CA	10.3%	83,985	39.9%	36.7%	22.8%	66.7%	33.9%	46.1%	4.6%	11.8%
Minneapolis-St. Paul, MN-WI	8.2%	83,698	43.2%	14.9%	10.6%	71.6%	5.9%	76.0%	8.6%	6.7%
Tampa-St. Petersburg, FL	12.4%	57,906	31.6%	22.6%	14.4%	60.3%	19.4%	63.0%	11.5%	3.5%
Denver-Aurora, CO	7.9%	85,641	45.8%	20.2%	11.9%	71.5%	23.1%	64.7%	5.5%	4.3%
Baltimore, MD	9.4%	83,160	41.9%	12.8%	10.3%	66.8%	5.9%	56.6%	28.8%	5.7%
St. Louis, MO-IL	9.9%	66,417	35.8%	6.7%	4.8%	65.3%	3.0%	73.8%	18.1%	2.6%

where  $y_{it}$  is the dependent variable, i.e. YoY ridership reduction rate for the metropolitan area  $i$  ( $i = 1 \dots 20$ ) during the month  $t$  ( $t = 1 \dots 12$ );  $X_{it}$  is the vector of independent variables as listed in Table 2; In the panel data model, there are two types of independent variables: (1) the individual-specific variables which are specific to the individual metropolitan area  $i$  and to be constant over time (during the different months), such as the sociodemographic variables listed in Table 2; and (2) time-variant variables which will change over time, such as the COVID-19 Composite Index;  $\alpha_i$  is the individual effect which is specific to the individual metropolitan area  $i$  and to be constant over time;  $\varepsilon_{it}$  is the error term and  $\beta$  are the coefficient vectors for  $X_{it}$ .

In general, there are two types of panel data models: the fixed-effects model and the random-effects model. The random-effects model assumes that the individual-specific effects  $\alpha_i$  are distributed independently of the independent variables while the fixed effects model allows  $\alpha_i$  being correlated with the independent variables. In the random-effects model,  $\alpha_i$  is included as a part of the error term, and in the fixed effects model,  $\alpha_i$  is included as an individual specific intercept for the metropolitan area  $i$ . The fixed-effects model has the advantage of not requiring  $\alpha_i$  to be independent with  $X_{it}$ , which is often difficult to verify. However, the standard fixed-effects model cannot identify the effects of any individual-specific variables because it requires the within-group variation for model estimation (Qi et al., 2007). The Hausman test can be used to choose between a fixed-effect model or a random-effect model (Greene, 2000). The null hypothesis is that random-effects is the favored model and the alternate hypothesis is that fixed-effects is the favored model. In this study, the  $p$ -value of the Hausman test is 0.5526. Since it is greater than the 5% significant level, the null hypothesis cannot be rejected, which indicates that the random-effects model should be selected.

From the independent variables that list in Table 2, it can be seen that some of the sociodemographic factors may be highly be correlated. For example, the areas with a high percentage of poverty tend to have low median household income (negative correlated) and the areas that have a high percentage of the non-English speaking population may also have a high percentage of the foreign-born population (positively correlated). The high correlations between two or more independent variables will cause the multicollinearity problem in a regression model. To detect multicollinearity, variance inflation factors (VIF) of the selected independent variables were calculated and the variables with VIF valuable greater than 2.5 were removed from the model one by one (Johnston et al., 2018). The VIF based multicollinearity analysis results were presented in Table 5 and it was found that only 4 variables can be included in the model.

After that, according to the  $P$ -values of the independent variables from the regression modeling results, the final set of independent variables that have significant impacts on the dependent variable can be identified and the results of the developed final random-effects panel data model are presented in Table 6. It can be seen that there are only two independent variables that are significantly associated with the reduction of transit ridership during the COVID-19 pandemic. They are the COVID-19 Composite Index (CI) and Percentage of Bachelor's degree or higher. The Goodness-of-fit indexes R-squared is 0.69197, indicating the random effects regression fitted the data well.

From the modeling results presented in Table 6, it was found that the ridership reduction rate increased as the COVID-19 CI increased, and the areas with a high percentage of the population with a bachelor's degree or higher tend to have more transit ridership reductions during the COVID-19 pandemic. More specifically, with all other variables keeping constant, 1 unit increase in COVID-19 CI is associated with 1% more reduction in transit ridership. Similarly, 1% increase of the population with a B.S. degree or higher is associated with about 1.06% more reduction in public transit ridership during the COVID-19 pandemic.

These findings are reasonable and consistent with the findings in the literature. First, the COVID-19 CI measures the level of fear toward COVID-19 in an area. As the level of such fear increases, the public will avoid using public transit to reduce their exposure to the COVID-19 risk, thereby reduction of public transit ridership will increase. Second, as we mentioned in the literature review section, previous studies (Hu and Chen, 2021 and Brough et al., 2020) also found that the transit ridership declined more among the higher educated individuals. The major reason is that individuals with higher education are less likely to engage in jobs that involve a high physical presence and therefore more likely to be able to work remotely (Dingel and Neiman, 2020). On the other hand, the less educated individuals are more likely to work in grocery stores, sanitation, and cleaning, and logistics and are often labeled "essential" workers who are still required to travel to their place of work during the pandemic. Therefore, the difference in the percentage of the population with a B.S. degree or higher becomes a key contributor to the socioeconomic disparities in travel behavior during the pandemic.

**Table 5**  
Selected Independent Variables Based on Multicollinearity Analysis.

Variable	VIF
CI	1.001494
Percentage of Bachelor's degree or higher	1.193229
Percentage of Hispanic	1.327218
Percentage of Black	1.203261

**Table 6**

Results of the Random Effects Panel Model.

Variable	Coeff.*	Std. Error	Z value	P-value
CI	0.01021119	0.00045213	22.5848	< 2.2e-16
Percentage of Bachelor's degree or higher	1.05677359	0.22206443	4.7589	1.95E-06
Intercept	−0.33264141	0.09184855	−3.6216	0.0002928
R-Squared	0.69197			
Adj. R-Squared	0.68937			
Chi-squared	532.411 (df = 2); p-value: < 2.22e-16			
Sample size	240			

**Table 7**

Correlation Analysis.

Variables	Correlation with Dependent Variable	P-value
Median Household Income	0.277235844	1.3112E-05
Percent In Poverty	−0.210951458	0.00100879
Percentage of Bachelor's degree or higher	0.287724398	5.89E-06
Percentage of Employment Rate	0.190918186	0.00298175
Percentage of Hispanics	−0.157367352	0.01467014
Percentage of Asian	0.171722571	0.00767003

### Correlation analysis

Although the regression model can account for the collective effects of multiple variables, only a few independent variables can be included in the model and identified as variables having significant impacts on the dependent variable. To further investigate the impacts of different independent variables, the traditional correlation analysis method was also used to further identify the factors that are significantly correlated with the dependent variable. For this purpose, the Pearson correlation coefficients between the independent variables and the dependent variable (i.e. YoY ridership reduction rate) were calculated and the results are presented in Table 7, where the independent variables that have significant correlations with the ridership reduction were listed.

From Table 7, it can be seen that six variables are significantly correlated with the public transit ridership reduction during the COVID-19. Following are some key findings:

- The median household income, percentage of bachelor's degree or higher, percentage of employment rate, and percentage of Asians have positive correlations with the public transit ridership reduction. It means that the areas with higher median household income, a higher percentage of the population with a Bachelor's degree or higher, higher employment rate, and a higher percentage of the Asian population have more reductions in public transit ridership.
- The percent in poverty and percentage of Hispanics have negative correlations with the public transit ridership reduction. It means that the areas with a higher percentage of the population in poverty, and a higher percentage of the Hispanic population tend to have less reduction in public transit ridership.

Among these findings, the findings regarding household income are consistent with the findings in the literature. Brough et al.(2020), Wilbur et al. (2021), and Hu and Chen (2021) all found that the transit ridership in high-income areas has dropped more than in low-income areas during the COVID-19 pandemic.

### Conclusion

In this study, a national-wide study is conducted to investigate the impacts of COVID-19 on the public transit ridership in the top twenty metropolitan areas in the US. At first, the reasons for the ridership decline during the COVID-19 pandemic were discussed based on the findings from the literature. After that, a COVID-19 composite index was developed to qualitatively measure the level of public fear toward COVID-19 in different metropolitan areas. Next, a random-effects panel data model was developed to analyze the impacts of COVID-19 and some socioeconomic factors on transit ridership reduction during the COVID-19 pandemic. In addition, correlation analysis was conducted to further analyze the impacts of the identified socioeconomic factors.

### Key findings

According to the results of this study, the following key findings can be obtained:

- The transit ridership for all areas has been reduced significantly, but the reduction rate varies by time and area.
- The level of public fear toward COVID-19 of a metropolitan area has significant impacts on its public transit ridership reduction. Specifically, 1 unit increase in COVID-19 CI is associated with 1% increase in the reduction of transit ridership.
- For different socioeconomic groups, the changes in transit ridership during the COVID-19 pandemic are different:
  - Areas with a high percentage of the population with a bachelor's degree or higher tend to have more transit ridership reductions. Specifically, 1% increase of the population with a B.S. degree or higher is associated with about 1.06% increase in the reduction of public transit ridership.
  - Areas with higher median household income, higher employment rate, and a higher percentage of the Asian population are more likely to have more reductions in public transit ridership.
  - Areas with a higher percentage of the population in poverty, and a higher percentage of the Hispanic population are more likely to experience smaller reductions in public transit ridership.

### Policy implications

The findings of this study can help public transit agencies and local transportation planning organizations better understand the causes and patterns of changes in public transit ridership during the pandemic. Note that, the developed model can be applied to predict the transit ridership for any area of any size because all the dependent and independent variables (including the COVID-19 composite index) used in the model have relative values instead of absolute values. Based on the predicted ridership change, the transit agencies can adjust their service by adding more service in the area where more population depends on the public transit while reducing their service in the areas where a high proportion of the population can choose to work from home or shift to other transportation modes. In addition, the local government can also allocate more public transit funding to the areas where a higher percentage of the population depends on public transit to better accommodate their travel needs during the pandemic. Overall, the results of the study can help the public transit agencies and local transportation planning organizations make the right decisions to fully consider both equity and efficiency issues in the public transit system during the pandemic.

### Limitations and future study needs

There are several limitations of this study. First, there are some other unobserved factors like government policies and vaccination rates, that may also contribute to the change of public transit ridership. In the future, more data need to be collected to consider the impacts of the vaccination rate and other factors on the recovery of public transit ridership. Second, the data in this study was collected at an aggregated metropolitan-area level which makes it hard to differentiate the significance of the socioeconomic factors. In the future, more disaggregated data need to be collected to further investigate the impacts of socioeconomic factors. Furthermore, this study only analyzed the top 20 metropolitan areas in the US. In the future, data from more metropolitan areas need to be collected to improve the results of this study.

### Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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